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Collaborative Spectral Decision Process for Cognitive Wireless Networks Using Bio-inspired Optimization

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Abstract

The latest advances in wireless technologies address some of the major limitations of today's wireless communication systems. Cognitive radio is a field that establishes through a set of strategies, methodologies to improve the use of the radioelectric electromagnetic spectrum. This work evaluates spectral mobility in a cognitive radio network when implementing a collaborative access strategy and a decision-making process based on genetic algorithms. The analysis is performed for three levels of collaboration based on the cumulative Handoff Number, cumulative Failed Handoffs, cumulative Average Delay, Average Throughput y Average Bandwidth. The results show that the level of collaboration of 80 % presented the best performance, compared to the level of collaboration of 40 %, the highest percentage ratio obtained was 23 % and the lowest was 4.8 %. This indicates that the level of collaboration that leads to efficient results is between 40 % and 80 %.

Keywords: Cognitive Radio Network, Collaborative Spectral Decision, Genetic Algorithms, Spectral mobility

I. INTRODUCTION

Cognitive radio (CR) is a key technology to overcome the disadvantages of static spectrum allocation and improve utilization through dynamic spectrum access techniques. [1], [2]. It is an emerging technology that since the last decade has been identified as a natural extension of wireless networks [3].

The objective of a CR is to access the spectrum dynamically, through opportunistic exploration in the spatial and temporal dimensions of the network. In cognitive networks there are two types of users, the primary user (PU) who pays to use a licensed frequency band and the unlicensed or secondary user (SU) who makes opportunistic use of the spectrum while it is available [4].

To implement dynamic and opportunistic access, cognitive radio networks (CRN) work with a management model called the cognitive cycle, this model allows for intelligent adaptations, through learning and the exchange of information. Fig. 1 presents the cognitive cycle of a CRN [5]–[7].

The main challenge for CRN is to guarantee the QoS requirements without causing degradation in the communication performance of the PU. There are various strategies available, however, collaborative algorithms are currently gaining a strong boost for applications with cognitive structures [8], [9].

In the context of CRN, collaborative strategies allow users to communicate with each other to exchange locally observed interference measurements, the objective is to take advantage of spatial diversity, to achieve this, the unlicensed user shares his detection information with neighboring users [10]–[12].

Fig. 2 shows a collaborative structure in a centralized way, there is a Central Unit (CU) in charge of coordinating the process [10], [13]. The CU selects the spectral opportunity and informs all cooperating SU to individually perform local detection and the results are sent through the control channel. Finally, the CU analyzes the information received, determines the presence of PU and disseminates the decision to the cooperating SU [13].

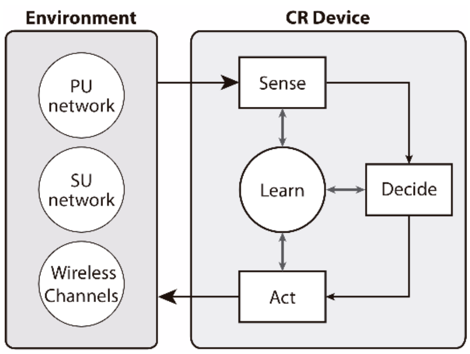

Fig. 1. CRN cognitive cycle

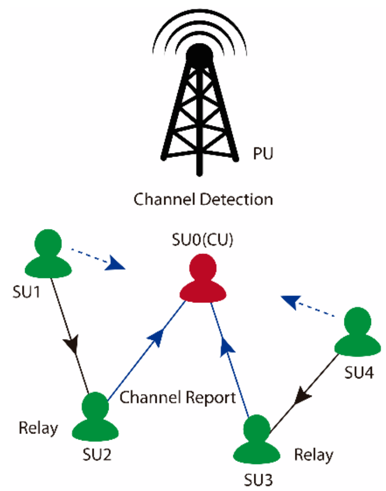

Fig. 2. Structure of a collaborative strategy

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I.I Inspired Optimization Models

Bio-inspired optimization draws inspiration from natural phenomena [14]. During the last few years, these techniques have been implemented in different areas of engineering, due to the fact that they present efficient performances and viable solutions to complex problems [3], [8], [15].

Genetic algorithms are models inspired by the genetics process, a simple model is made up of an initial population of individuals and a set of operations that interact on the population to obtain new generations of individuals [3], [14]

The population is made up of a set of individuals represented by an equivalent in binary number, the binary representation is called "Chromosome" and each bit within the chromosome is called "Gene". A genetic algorithm is characterized through five definitions or genetic equivalents, which are described in Table 1. Fig. 3 presents a description for a specific population.

Table 1: Characteristics of a genetic structure

Genetic Parameter	Description
Allele	Each of the different states that a gene can present in the same position.
Gen	It is the value of an allele within an array.
Chromosome	It is a collection of genes in the form of an arrangement.
Position	It is the place that a gene occupies within the chromosome.
Index	It is the position that the individual has within the population.

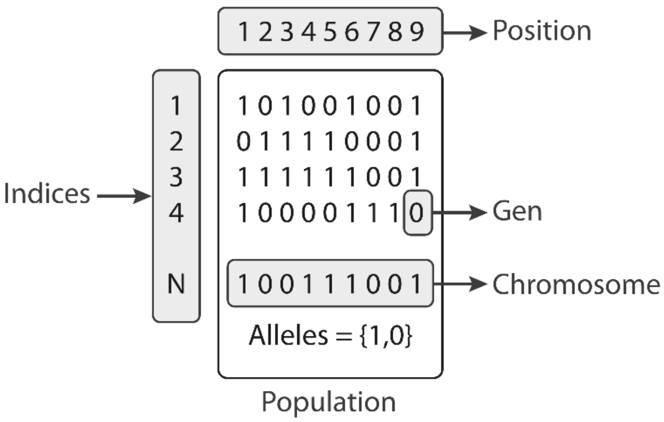

Fig. 3. Genetic equivalents specific population [16]

The objective of this work is to evaluate spectral mobility in a CRN according to three levels of collaboration, these levels are characterized through the amount of information that SU share before accessing the spectrum. For the level of shared information, the radio environment is segmented through three levels of collaboration (10 %, 40 % and 80 %). For the analysis of spectral mobility, a decision-making strategy based on genetic algorithms is implemented.

This work is organized in four sections including the introduction. Section 2 presents the methodology, describes the structure to be implemented, the input variables, the decision-making algorithm and the performance metrics. Section 3 presents the results obtained and the respective discussion. Finally, section 4 presents the conclusions of the work.

II. METHOD

Fig. 4 presents the block diagram of the implemented strategy. Where:

- *Input data:* Characterization of the radio environment, which is carried out through the spectral occupation, obtained by a monitoring system.
- *Decision Making:* Bio-inspired decision-making model, a genetic algorithm is used to establish the access decision methodology to the SU channel.
- *Spectral Mobility:* Analyzes channel changes according to SU channel access decisions.
- *Performance Metrics:* Generates the performance metrics: Cumulative Handoff Number, Cumulative Failed Handoffs, Cumulative Average Delay, Average Throughput y Average Bandwidth.

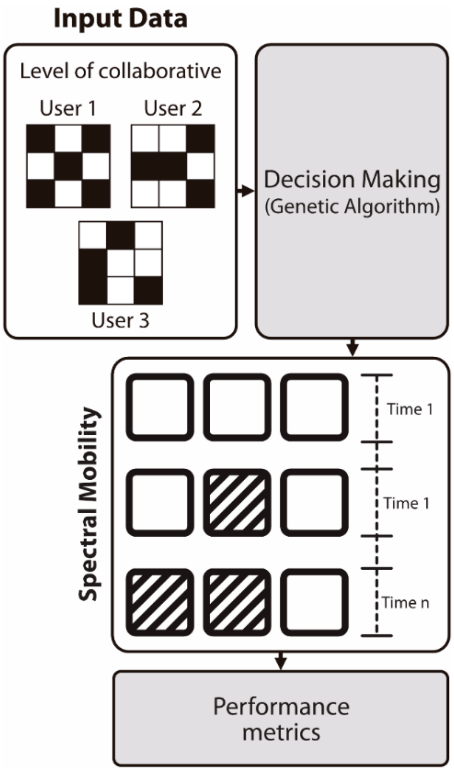

Fig. 4. Block diagram of the implemented strategy

The description of each of the blocks is detailed in the following sections.

II.I Input Data

To evaluate the performance of the proposed strategy, a radio environment is used with real information on the behavior of the PUs. This information corresponds to a spectral power matrix in the Wi-Fi frequency band. Which is obtained through a measurement process using the energy detection technique. Table 2 describes the size of the spectral power matrix.

Table 2: Matrix of measured spectral power

Frequency band	Rows (time)	Columns (channels)	Total Data
Wi-Fi	2.490.000	550	1.369.500.000

The structure of the collaborative model implemented consists of dividing the spectral power matrix into sub-matrices (Fig. 5) and characterizing the collaboration levels according to the number of users that will be part of the analysis of the spectral decision process (Fig. 6).

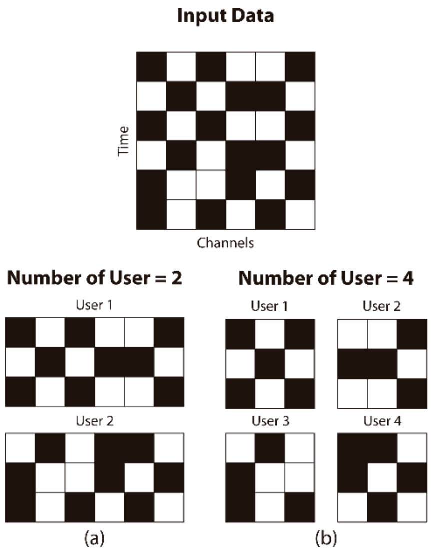

Fig. 5. Division methodology according to the number of users

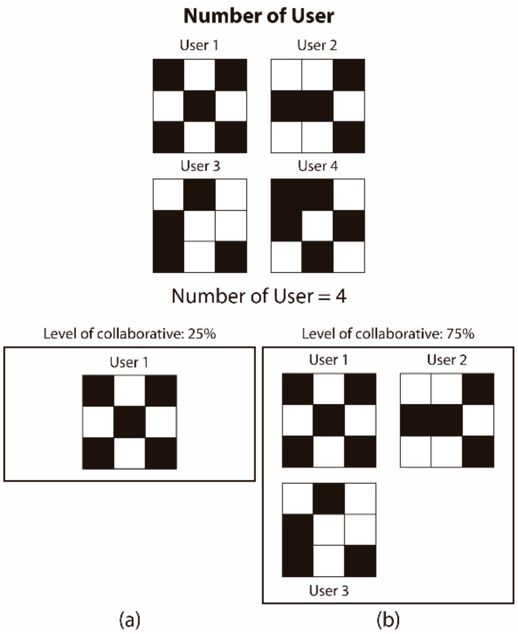

Fig. 6. Collaboration levels methodology

Fig. 5 describes the methodology used for the division of the radio environment characterization matrix. The spectral power matrix is taken and divided according to the number of users (sub-matrices). For example, Fig. 5 (a) and Fig. 5 (b) present the division implemented if it is required to characterize the radio environment in two and four users respectively. For this work, a division of 100 users (subarrays = 100) was selected.

After the division of the spectral power matrix, the amount of information to be shared is established. Fig. 6 describes the methodology used, the sub-matrices obtained are taken and according to the level or percentage of collaboration the number of users is selected, a parameter equivalent to the amount of information to be shared. For example, in Fig. 6 the division process generated four users (sub-matrices), if a collaboration level of 25 % is selected (Fig. 6 (a)), the information to be shared corresponds to the information of a single user; If a collaboration level of 75 % is selected (Fig. 6 (b)), the information to be shared corresponds to the information of three users. For this work, three levels of collaboration were selected: 10 %, 40 % and 80 %.

II.II Decision Making: Genetic Algorithm

To analyze the spectral mobility in a CRN according to collaborative strategies and bio-inspired decision making, the cross-validation technique is used. Therefore, the implementation of two matrices is required, one for training and the other for the evaluation of the model. For the evaluation matrix, the information measured with the energy detection technique is used. The training matrix is designed through a genetic algorithm, later it will be the matrix to which the division methodology and collaboration levels will be implemented. To obtain the training matrix using genetic algorithms, it begins by establishing a random initial population, which, through selection, crossing and mutation, generates the training matrix. The number of generations (iterations) is adjusted with trial and error criteria, taking into account simulation times and computational load. Fig. 7 presents the flow diagram of the genetic algorithm used for the training matrix.

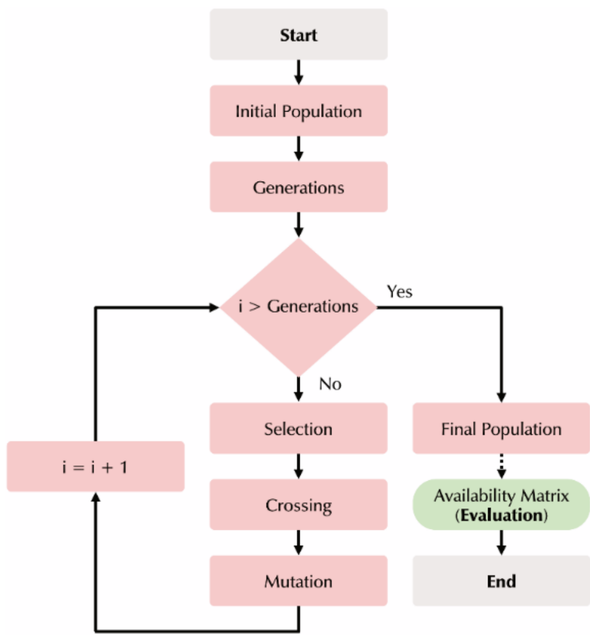

Fig. 7. Genetic algorithm flow chart

II.II.I Spectral Mobility

Spectral mobility is the process in which a cognitive radio SU changes its channel of operation. The process by which the SU changes from one frequency channel to another is known as spectral handoff. [17]. In order to analyze spectral mobility, the power matrix is transformed into an availability matrix, this conversion is carried out through a threshold criterion, which was set at -95 dBm. The availability matrix is the radio environment where the spectral mobility process can be quantified.

From the decision-making process, each channel in the availability matrix is assigned a score, the channels with the highest spectral opportunities have the highest scores and the channels with the least spectral opportunities have the lowest scores. The objective is for the SU to make jumps in the availability matrix (channel changes) according to the information from the scores. When performing the channel hops, if the SU finds a spectral opportunity, it automatically makes a new jump, but to the next row of the availability matrix. The information of the changes or jumps is stored and used to generate performance metrics. The metrics correspond to the figures of: Cumulative Handoff Number, Cumulative Failed Handoffs, Cumulative Average Delay, Average Throughput y Average Bandwidth.

III. RESULT

The results achieved are presented through the metrics associated with the performance of the decision-making algorithm and the levels of collaboration during a 9-minute transmission. The implementation was done on a computer with a 2.8 GHz Intel (R) Core (TM) i7-7700HQ processor with 24 GB of RAM, Microsoft Windows 10 64-bit operating system using MATLAB version R2020a.

Fig. 8, Fig. 9 and Fig. 10 show the behavior for the number of handoffs, missed handoffs and average delay respectively. For these metrics, the best performance is obtained with the lowest indicators, the lowest performance is obtained with the highest indicators. According to the results obtained, the collaboration levels of 80 % and 40 % generated the best performances and the collaboration level of 10 % presented the lowest performance.

Fig. 11 and Fig. 12 show the behavior for the average Throughput and the average bandwidth respectively. For these metrics, the best performance is obtained with the highest indicators, the lowest performance is obtained with the lowest indicators. According to the results obtained, the collaboration level of 80 % presented the best performance and the collaboration level of 10 % presented the lowest performance.

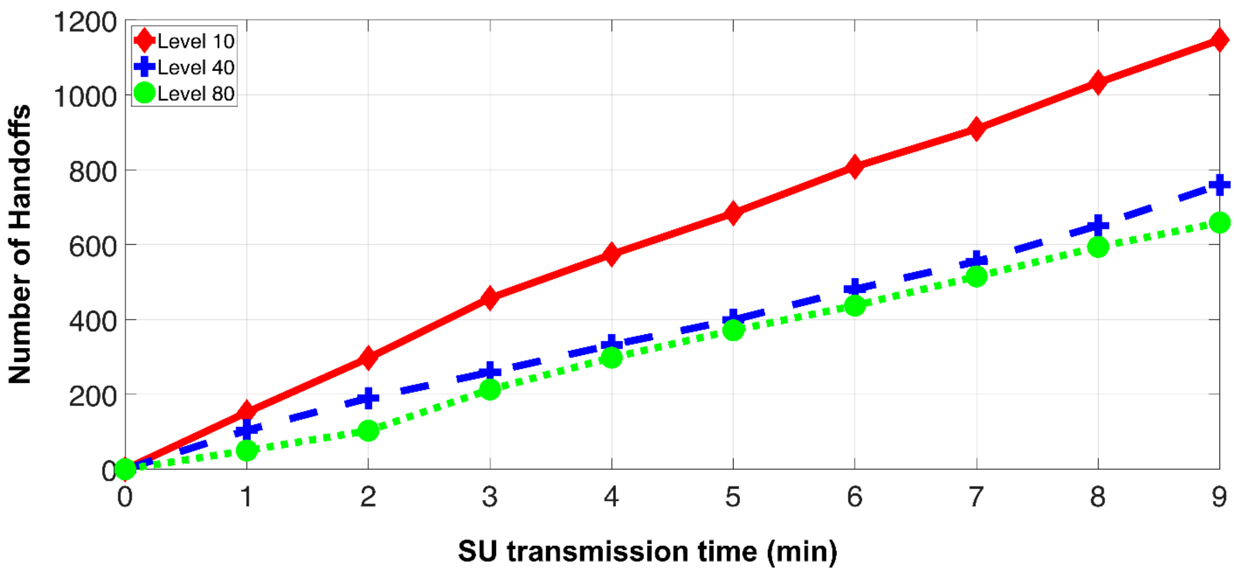

Fig. 8. Cumulative Handoff Number

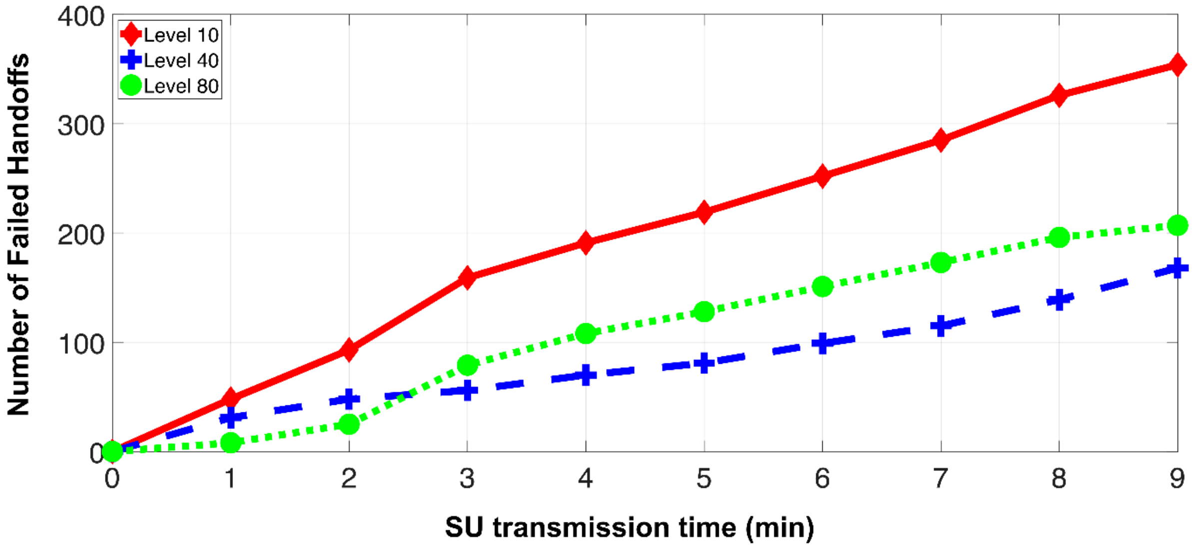

Fig. 9. Cumulative Failed Handoffs

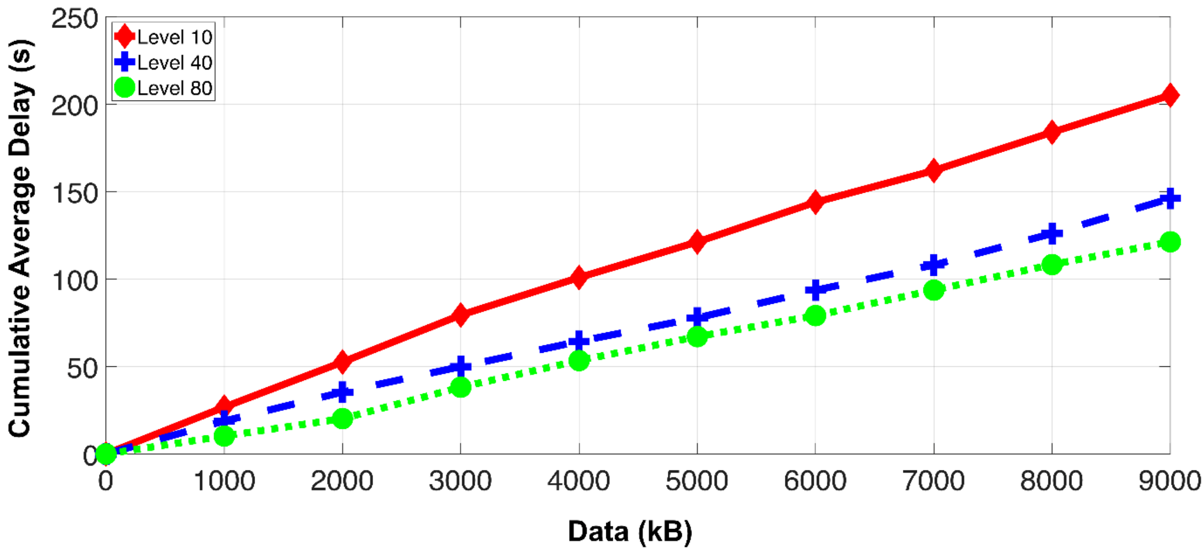

Fig. 10. Cumulative Average Delay

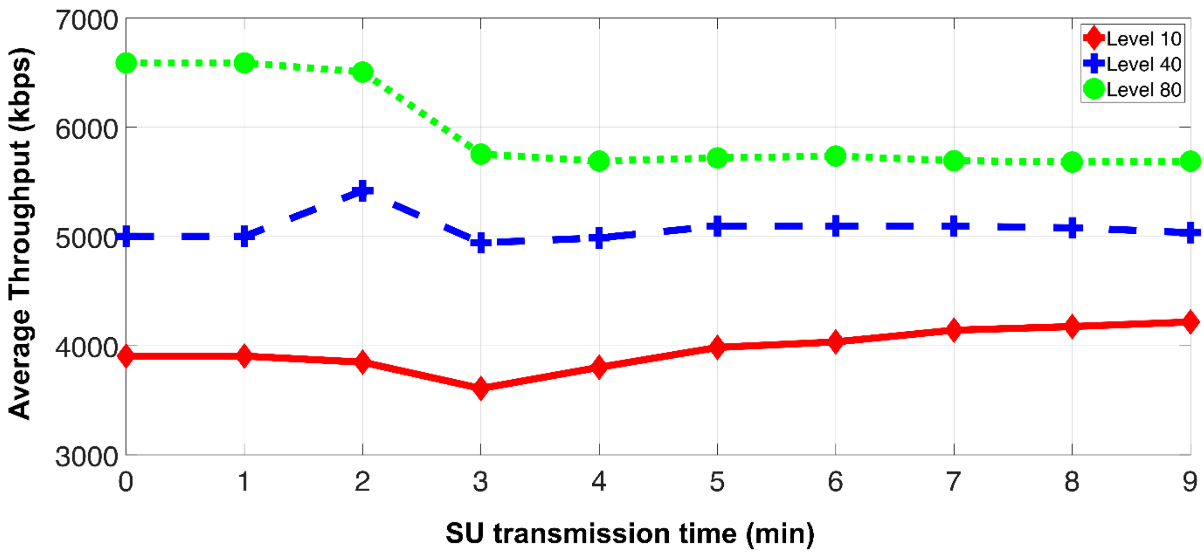

Fig. 11. Average Throughput

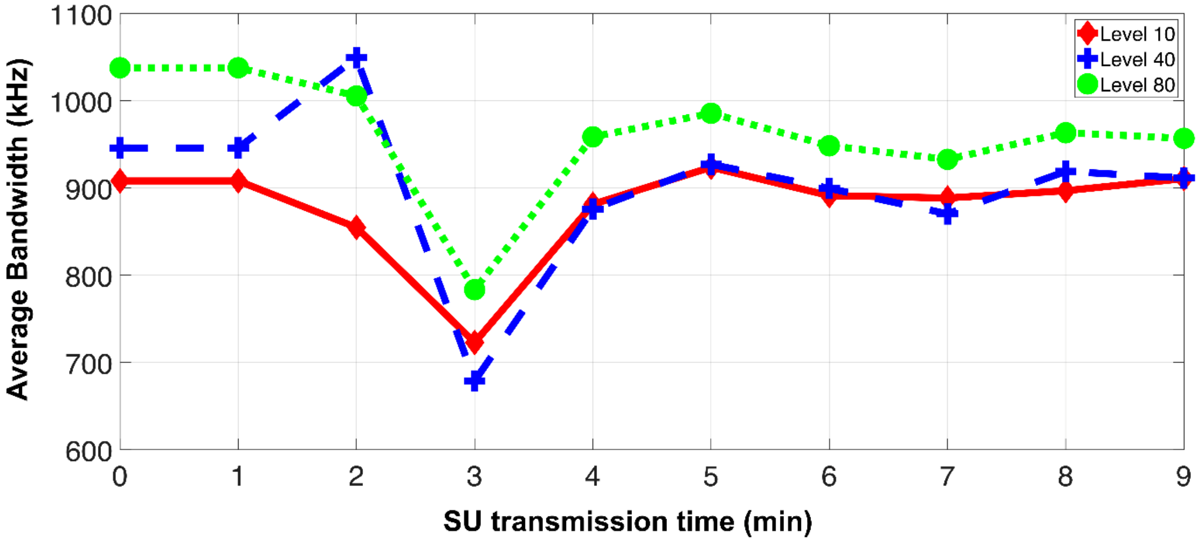

Fig. 12. Average Bandwidth

III.I Discussion

The analysis and discussion of the performance metrics is carried out for the total accumulated in the 9 minutes of transmission of the SU. For the delay they correspond to the total average time experienced by the SU during the transmission of 9000 kB.

Table 3 presents the percentage increase obtained for the number of Handoffs and Failed Handoffs as a function of the collaboration levels. For the number of Handoffs, the level of collaboration of 80 % is used as a base, which presented the highest performance, an increase in the number of Handoffs of 15 % is identified for the level of collaboration of 40% and 74% for the collaboration level of 10 %. For the number of Failed Handoffs, the level of collaboration of 40 % is used as a base, which presented the highest performance, an increase in the number of Failed Handoffs of 23 % is identified for the level of collaboration of 80% and 111 % for the 10% collaboration level.

Table 3: Increase in the number of Handoffs and Failed Handoffs based on the best level of collaboration

Metrics	Collaboration Level		
	10 %	40 %	10 %
Handoffs	74	15	-
Failed Handoffs	111	-	23

Table 4 presents the percentage increase obtained for the Delay as a function of the collaboration levels. The 80 % collaboration level is used as a base, which presented the highest performance. An increase in delay of 20 % is identified for the 40 % collaboration level and 69 % for the 10 % collaboration level.

Table 4: Delay increase based on the best level of collaboration

Metrics	Collaboration Level		
	10 %	40 %	10 %
Delay	69	20	-

Table 5 presents the percentage increase obtained for Throughput and Average bandwidth as a function of collaboration levels. The 80 % collaboration level is used as a base, which presented the highest performance. A decrease in Throughput of 12 % is identified for the 40 % collaboration level and 26 % for the 10 % collaboration level. A 4.8 % decrease in Average bandwidth is identified for the two levels of collaboration.

Table 5: Throughput and Average bandwidth decrease depending on the best level of collaboration

Metrics	Collaboration Level		
	10 %	40 %	80 %
Throughput	26	12	0
Average bandwidth	4.8	4.8	0

IV. CONCLUSION

Cognitive radio is a key technology to overcome the problems generated by fixed spectrum allocation policies. There are various strategies available, collaborative algorithms are currently gaining a strong boost for applications with cognitive structures. This work analyzed spectral mobility according to three levels of collaboration: 10 %, 40 % and 80 %. The collaboration level of 80 % presented the best performance in all scenarios, however, with respect to the collaboration level of 40 %, the highest percentage ratio obtained was 23 % and the lowest was 4.8 %. This indicates that the level of collaboration that leads to efficient results is between 40 % and 80 %.

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